## REMARKS

Claims 20-24, 26-31, 33 and 40-45 are pending in the present application. Applicants respectfully request reconsideration of the application in view of the above amendments and remarks made herein.

Claim 27 has been amended to claim, *inter alia*, "a computer readable medium embodying instructions executed by a processor to perform method steps for processing multimedia data in a computer system." Claims 28-31 and 33 have been similarly amended. These amendment have been made to advance prosecution by using a form of a Beauregard type claim recognized in the MPEP (MPEP 2106.01).

## I. Rejections Under 35 U.S.C. § 103

Claims 20-24, 26-31 and 33 are rejected under 35 U.S.C. § 103(a) as being unpatentable over Non Patent Literature (NPL) "Dynamic Generation and Refinement of Concept Hierarchies for Knowledge Discovery in Databases" by *Han et al.* (hereinafter "*Han*") in view of NPL "An Environment for Content-Based Image Retrieval From Large Spatial Databases by *Agouris et al.* (hereinafter "*Agouris*"). The Examiner stated essentially that the combination of *Han* and *Agouris* teaches or suggests all of the limitations of Claims 20-24, 26-31 and 33.

Claims 20 and 27 are the independent claims.

Claim 20 claims, *inter alia*, "joining the results to obtain a match combination according to a matching algorithm, by determining an assignment for the child-concepts, subject to the inter-sibling constraints and the weights corresponding to the child-concepts."

*Han* teaches applying a knowledge discovery algorithm on data stored in a database, with the assistance of concept hierarchy information (see page 166, section 5.2). *Han* does not teach or suggest "joining the results to obtain a match combination according to a matching algorithm, by determining an assignment for the child-concepts, subject to the inter-sibling constraints and the weights corresponding to the child-concepts" as claimed in Claim 20. Consider that *Han* merely teaches that the outputs obtained by applying the knowledge discovery algorithm are generalized relations or knowledge rules extracted from the database (see page 166, section 5.2). Further, *Han* is silent on inter-sibling constraints and weights corresponding to child-concepts. Thus, it follows that *Han* does not teach or suggest "joining the results to obtain a match combination according to a matching algorithm, by determining an assignment for the child-concepts, subject to the inter-sibling constraints and the weights corresponding to the child-concepts" as claimed in Claim 20. Therefore, *Han* fails to teach or suggest all of the limitations of Claim 20.

*Agouris* teaches matching a query sketch of a feature against features at the parent level in a tree, then progressing to the child level, the grandchild level, and other levels as necessary (see page 267, column 1, paragraph 2). *Agouris* does not teach or suggest "joining the results to obtain a match combination according to a matching algorithm, by determining an assignment for the child-concepts, subject to the inter-sibling constraints and the weights corresponding to the child-concepts" as claimed in Claim 20. Consider that *Agouris* teaches comparing a new feature to existing features and progressing through tree levels until the new feature is eventually matched to an entry of the tree, or inserted into the tree (see page 268, column 1, paragraph 3). That is, *Agouris* teaches matching a single query feature to a single feature in a database. Nowhere does *Agouris* teach or suggest joining results to obtain a match combination, let alone doing so by

determining an assignment for child-concepts subject to inter-sibling constraints and weights, essentially as claimed in Claim 20. Thus, *Agouris* fails to cure the deficiencies of *Han*.

The combination of *Han* and *Agouris* teaches applying a knowledge discovery algorithm on data stored in a database, with the assistance of concept hierarchy information, and matching a query sketch of a feature against features at the parent level in a tree, then progressing to the child level, the grandchild level, and other levels as necessary. The combination does not teach or suggest "joining the results to obtain a match combination according to a matching algorithm, by determining an assignment for the child-concepts, subject to the inter-sibling constraints and the weights corresponding to the child-concepts" as claimed in Claim 20. Accordingly, the combination does not teach or suggest all of the limitations of Claim 20.

Claim 20 further claims, *inter alia*, "wherein each aggregation edge is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and relative importance corresponds to relevance of a child-concept to a definition of the high-level concept."

*Han* teaches algorithms for automatic generation of concept hierarchies for numerical attributes based on data distributions (see Abstract). *Han* does not teach or suggest "wherein each aggregation edge is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and relative importance corresponds to relevance of a child-concept to a definition of the high-level concept" as claimed in Claim 20. *Han* teaches an occurrence count of a node which, if a leaf node, represents the number of occurrences of the value in the task-relevant data set, or if a nonleaf node, the sum of the occurrence count of its children nodes (see page 161, Definition 3.1). For example, in Figure 2 on page 164, node Maritime has 3 child

nodes, each with an occurrence count of 15, 9 and 9, respectively. Thus, the occurrence count of Maritime is the sum of its children nodes: 33. This is clearly not analogous to assigning a weight to an aggregation edge, essentially as claimed in Claim 20. Thus, *Han* fails to teach or suggest all of the limitations of Claim 20.

*Agouris* teaches content-based image retrieval using queries on shape and topology (see Abstract). *Agouris* does not teach or suggest "wherein each aggregation edge is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and relative importance corresponds to relevance of a child-concept to a definition of the high-level concept" as claimed in Claim 20. *Agouris* teaches a hierarchical (tree-like) structure as a progressive filtering mechanism. A query feature is first matched against each of the features at the parent level in the tree (see page 267, column 1, paragraph 2). When a query is performed, the matching percentage between the query feature and a parent feature falls in one of three ranges: 0-49%, 50-79% and 80-100% (see page 267, column 2, paragraph 1). If the matching percentage is in the 50-79% range, the query feature is considered to be 'similar' to that parent feature, and the query feature is then tested against this parent feature's respective child features (see page 267, column 2, paragraph 2). That is, <u>each parent-child edge always corresponds to a matching percentage of 50-79%; they are not assigned a weight</u> (see also FIG. 4). This is clearly not analogous to Claim 20. In Claim 20, <u>each aggregation edge (parent-child edge) is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and relative importance corresponds to the relevance of a child-concept to a definition of the high-level concept</u>. Thus, an aggregation edge corresponding to a child-concept that is relatively more important than its siblings in the definition of the high-level concept (e.g., it is more relevant to the high-level concept than its siblings) will have a higher weight than an aggregation edge corresponding to a

sibling child-concept that is relatively less important (see paragraph [0061] and FIG. 3 of the Application). Compare FIG. 4 of *Agouris* and FIG. 3 of the Application:

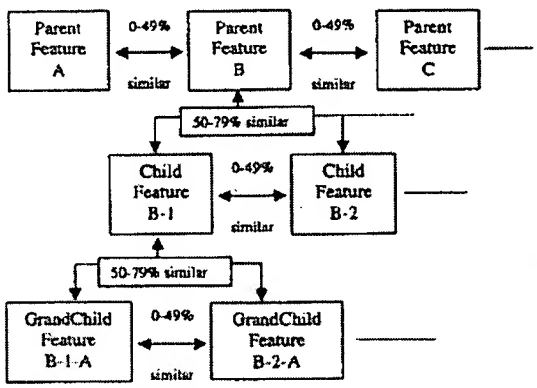


Fig. 4. Example of the feature library hierarchy.

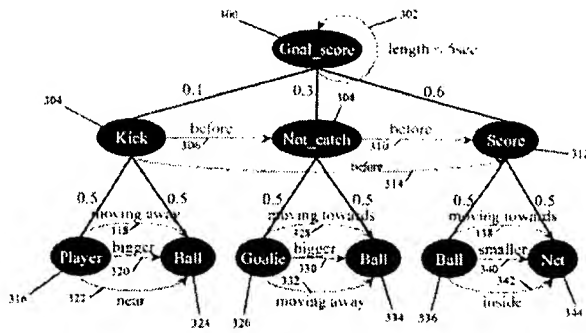


Figure 3

In FIG. 4 of *Agouris*, each parent-child edge between a parent (B) and its respective children (B-1, B-2) has the same value; a matching percentage range of 50-79%. Thus, <u>the edges between the parent and its children are not assigned a weight reflecting relative importance of each child in relation to its siblings and relative importance corresponds to the relevance of a child-concept to a definition of the high-level concept</u>. For example, in FIG. 4 of *Agouris*, once a query feature is considered to be 'similar' to the parent (e.g., the matching percentage is in the 50-79% range), it is compared with all of the parent's respective children; no child receives a preference over the others based on relative importance in relation to its siblings (see page 267, column 2, paragraph 2). In FIG. 3 of the Application, each aggregation edge (parent-child edge) is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and relative importance corresponds to the relevance of a child-concept to a definition of the high-level concept. For instance, for high-level concept Goal_score (300), child-concept Score (312) is the most relevant child-concept, followed by child-concept Not_catch (308) and child-concept

Kick (304). Thus, the aggregation edge connecting to Score (312) receives a weight of 0.6, the aggregation edge connecting to Not_catch (308) receives a weight of 0.3, and the aggregation edge connecting to Kick (304) receives a weight of 0.1. That is, the aggregation edges connecting to child-concepts are appropriately weighted so that the less relevant a child-concept is to the high-level concept, the less weight its corresponding aggregation edge has (see also paragraph [0061] of the Application). This is clearly not taught or suggested in *Agouris*, where <u>each parent-child edge corresponds to the same matching percentage range</u>. Thus, *Agouris* fails to cure the deficiencies of *Han*.

The combination of *Han* and *Agouris* teaches algorithms for automatic generation of concept hierarchies for numerical attributes based on data distributions and content-based image retrieval using queries on shape and topology. The combination does not teach or suggest "wherein each aggregation edge is assigned a weight reflecting relative importance of each child-concept in relation to its siblings" as claimed in Claim 20. Accordingly, the combination does not teach or suggest all of the limitations of Claim 20.

Claim 20 further claims, *inter alia*, "association edges between siblings that correspond to inter-sibling constraints."

*Han* teaches algorithms for automatic generation of concept hierarchies for numerical attributes based on data distributions (see Abstract). *Han* does not teach or suggest "association edges between siblings that correspond to inter-sibling constraints" as claimed in Claim 20. *Han* teaches edges between parent nodes and child nodes, but does not teach edges of any kind

between siblings, let alone edges between siblings that correspond to inter-sibling constraints (see Figure 2 on page 164). Thus, *Han* fails to teach or suggest all of the limitations of Claim 20.

*Agouris* teaches content-based image retrieval using queries on shape and topology (see Abstract). *Agouris* does not teach or suggest "association edges between siblings that correspond to inter-sibling constraints" (emphasis added) as claimed in Claim 20. The edges between siblings in *Agouris* represent a matching percentage range of 0-49% (see page 267 and FIG. 4), not inter-sibling constraints. For example, in *Agouris*, the edges between siblings always represent a matching percentage range of 0-49%. If a query feature matches a node in the 0-49% range, the query feature and the node are not a good match, and the edge signifies that the query feature should be checked against the node's siblings in an effort to find a better match. Thus, in *Agouris*, edges between siblings represent a global threshold that is the same for all siblings (e.g., 0-49%); the edges are not dependent upon the siblings they are connected to in any way. This is clearly not analogous to "association edges between siblings that correspond to inter-sibling constraints" (emphasis added) as claimed in Claim 20. Once again, compare FIG. 4 of *Agouris* and FIG. 3 of the Application:

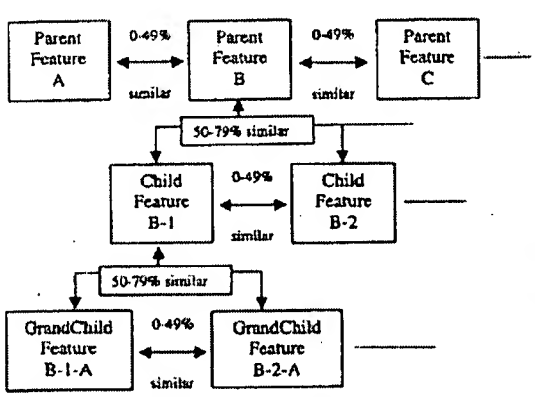


Fig. 4. Example of the feature library hierarchy.

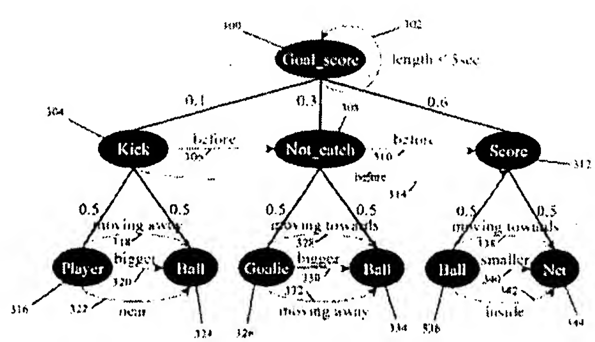


Figure 3

Unlike the edges between siblings in FIG. 4 of *Agouris*, which all represent a matching percentage range of 0-49%, the association edges between siblings in FIG. 3 of the Application correspond to inter-sibling constraints. That is, the association edges between siblings in FIG. 3 of the Application are more than merely a global threshold between all siblings. Rather, each association edge corresponds to inter-sibling constraints that are specific to the siblings that particular association edge connects to. For example, the association edges (318, 322) between sibling Player (316) and sibling Ball (324) are different from the association edges (338, 342) between sibling Ball (336) and sibling Net (344) (e.g., in the former set of siblings, Player (316) can either be 'moving away' (318) from Ball (324) or 'near' (322) Ball (324); in the latter set of siblings, Ball (336) can either be 'moving towards' (338) Net (344) or 'inside' (342) Net (344)). Thus, the association edges are different because they correspond to inter-sibling constraints, which is clearly not analogous to the global matching percentage range taught by *Agouris*. Therefore, *Agouris* fails to cure the deficiencies of *Han*.

The combination of *Han* and *Agouris* teaches algorithms for automatic generation of concept hierarchies for numerical attributes based on data distributions and content-based image retrieval using queries on shape and topology. The combination does not teach or suggest "association edges between siblings that correspond to inter-sibling constraints" as claimed in Claim 20. Accordingly, the combination does not teach or suggest all of the limitations of Claim 20.

Claim 27 includes certain limitations of Claim 20. For instance, Claim 27 claims, *inter alia*, "wherein each aggregation edge is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and the relative importance corresponds to a relevance of a child-concept to the high-level concept." Claim 27 further claims, *inter alia*, "association edges between siblings that correspond to inter-sibling constraints." Thus, Claim 27 is believed to be allowable for at least the reasons given for Claim 20.

Therefore, for at least the reasons above, Claims 20 and 27 are believed to be patentable and non-obvious over the combination of *Han* and *Agouris*. Applicants respectfully submit that inasmuch as Claims 21-24, 26, 28-31 and 33 are dependent on Claims 20 and 27, and Claims 20 and 27 are patentable over the cited references, Claims 21-24, 26, 28-31 and 33 are patentable as dependent on patentable independent claims. Withdrawal of the instant rejection is respectfully requested.

Referring to new Claims 40-45; Claim 40 includes certain limitations of Claim 20. For instance, Claim 40 claims, *inter alia*, "joining the results to obtain a match combination according to a matching algorithm, by determining an assignment for the child-concepts, subject to the inter-sibling constraints and the weights corresponding to the child-concepts." Claim 40 further claims, *inter alia*, "wherein each aggregation edge is assigned a weight reflecting relative importance of each child-concept in relation to its siblings and the relative importance corresponds to a relevance of a child-concept to the high-level concept." Claim 40 further claims, *inter alia*, "association edges between siblings that correspond to inter-sibling constraints." Thus, Claim 40 is believed to be allowable for at least the reasons given for Claim 20. Inasmuch as Claims 41-45

depend from Claim 40, and Claim 40 is believed to be patentable and non-obvious over the cited references, Claims 41-45 are believed to be patentable as dependent on a patentable independent claim. Allowance of Claims 40-45 is respectfully requested.

## CONCLUSION

In view of the foregoing, it is believed that all claims now pending patentability define the subject invention over the prior art of record and are in condition for allowance. Early and favorable reconsideration of the case is respectfully requested.

Respectfully submitted,

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